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Weather and Climate Extremes 9 (2015) 36–46

Contents lists available at ScienceDirect

Weather and Climate Extremes

journal homepage: www.elsevier.com/locate/wace

Unusual past dry and wet rainy seasons over Southern Africa and South America from a climate perspective

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ARTICLE INFO

Article history:
Received 23 December 2014
Received in revised form
9 July 2015
Accepted 11 July 2015
Available online 14 July 2015

Keywords:
Event attribution
Extreme precipitation
South Africa
South America
Climate change
Teleconnection

ABSTRACT

Southern Africa and Southern South America have experienced recent extremes in dry and wet rainy seasons which have caused severe socio-economic damages. Selected past extreme events are here studied, to estimate how human activity has changed the risk of the occurrence of such events, by applying an event attribution approach (Stott et al., 2004)comprising global climate models of Coupled Model Intercomparison Project 5 (CMIP5). Our assessment shows that models' representation of mean precipitation variability over Southern South America is not adequate to make a robust attribution statement about seasonal rainfall extremes in this region. Over Southern Africa, we show that unusually dry austral summers as occurred during 2002/2003 have become more likely, whereas unusually wet austral summers like that of 1999/2000 have become less likely due to anthropogenic climate change. There is some tentative evidence that the risk of extreme high 5-day precipitation totals (as observed in 1999/2000) have increased in the region. These results are consistent with CMIP5 models projecting a general drying trend over SAF during December–January–February (DJF) but also an increase in atmospheric moisture availability to feed heavy rainfall events when they do occur. Bootstrapping the confidence intervals of the fraction of attributable risk has demonstrated estimates of attributable risk are very uncertain, if the events are very rare. The study highlights some of the challenges in making an event attribution study for precipitation using seasonal precipitation and extreme 5-day precipitation totals and considering natural drivers such as ENSO in coupled ocean–atmosphere models.

1. Introduction

Human activity is affecting the occurrence and intensity of extreme weather events due to induced changes to the climate system (IPCC, 2013). Extreme events are of particular relevance to society because of their high impact on public and private sectors. The question therefore arises as to what degree human activity has contributed to a particular event (Allen, 2003). Recent studies have begun to address this question of event attribution by estimating how much particular extreme events can be explained by the changing climate (e.g. Stott and Allen, 2004; Pall et al., 2011; Rahmstorf and Coumou, 2011; Dole et al., 2011; Christidis et al., 2011; Lott et al., 2013). Approaches to attribute events remain diverse and there is an ongoing effort to synthesise attribution statements made by different studies (e.g. Otto et al., 2012; Peterson et al., 2013; Herring et al., 2014).

This study is an application of an event attribution methodology to particularly wet and dry rainy seasons in Southern Africa (SAF) and Southern South America (SSA). These are the seasons 2002/2003 (dry event) and 1999/2000 (wet event) for SAF (December to February) and the seasons 1988/1989 (dry event) and 1997/1998 (wet event) for SSA (October to March). The regions and events were selected during the World Climate Research Program (WCRP) – Abdus Salam International Centre for Theoretical Physics (ICTP) summer school on the prediction and attribution of extreme events. The majority of event attribution studies have so far focussed mainly on developed regions and to the best of the authors' knowledge only one has yet been published which considered events over South America (Shiogama et al., 2013), while there have been few studies over Africa (Lott et al., 2013; Otto et al.,

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http://dx.doi.org/10.1016/j.wace.2015.07.001

2013; Wolski et al., 2014 are representative of the few that have been made). This study therefore provides the opportunity to determine how anthropogenic climate change is affecting events in areas not previously extensively studied.

The event attribution is carried out using ensembles of general circulation models (GCMs) as first applied by Stott and Allen (2004) and also recently adopted to study extreme events over Australia (King et al., 2013; Lewis and Karoly, 2013). The ensembles are constructed using GCM integrations that consider both anthropogenic and natural forcings (ALL) and those that consider natural forcings only (NAT). The two ensembles (ALL and NAT) allow the estimation, from a model perspective, of how anthropogenic climate change has altered the likelihood of a certain threshold of a physical variable being exceeded at a certain point in time. This threshold is defined by a past observed extreme event.

The study further explores the sensitivities of an attribution study related to the definition of an extreme event, which is commonly an ambiguous step in an attribution study (Angélil et al., 2014). For example, an event such as a flood could be considered in terms of maximum precipitation rates or seasonal mean precipitation (Sippel and Otto, 2014). The consideration of natural variability when the event occurred is a further key assumption. Regional precipitation is affected by numerous natural variabilities, such as atmospheric teleconnections, and thus the consideration of natural drivers might alter the attribution statement. Differences in the description of an extreme precipitation event are therefore here translated into the effect on an attribution statement.

The paper is structured as follows: Section 2 provides background on precipitation climatologies over the two regions, the extreme events being studied and their socio-economic impacts. Section 3 describes in detail the underlying methodology and the model ensembles considered and Section 4 describes the results of the event attribution studies. In Section 5, discussion and the conclusions are presented.

2. Background on precipitation variability over study regions

2.1. Southern Africa

The climatological spatial distribution of accumulated rainfall for DJF for the period from 1975 to 2004 for Africa is shown in Fig. 1. Southern Africa is an austral summer (DJF) rainfall region, with the exception of the small winter rainfall area of the south west region and the narrow all year rainfall zone along the south coast. Rainfall over SAF is characterized by a west–east gradient. The main weather systems responsible for rainfall over the region have been presented in detail in Tyson and Preston-Whyte (2000). These systems include mesoscale convective systems, warm fronts, subtropical lows, mid- to upper-tropospheric troughs, cloud bands,

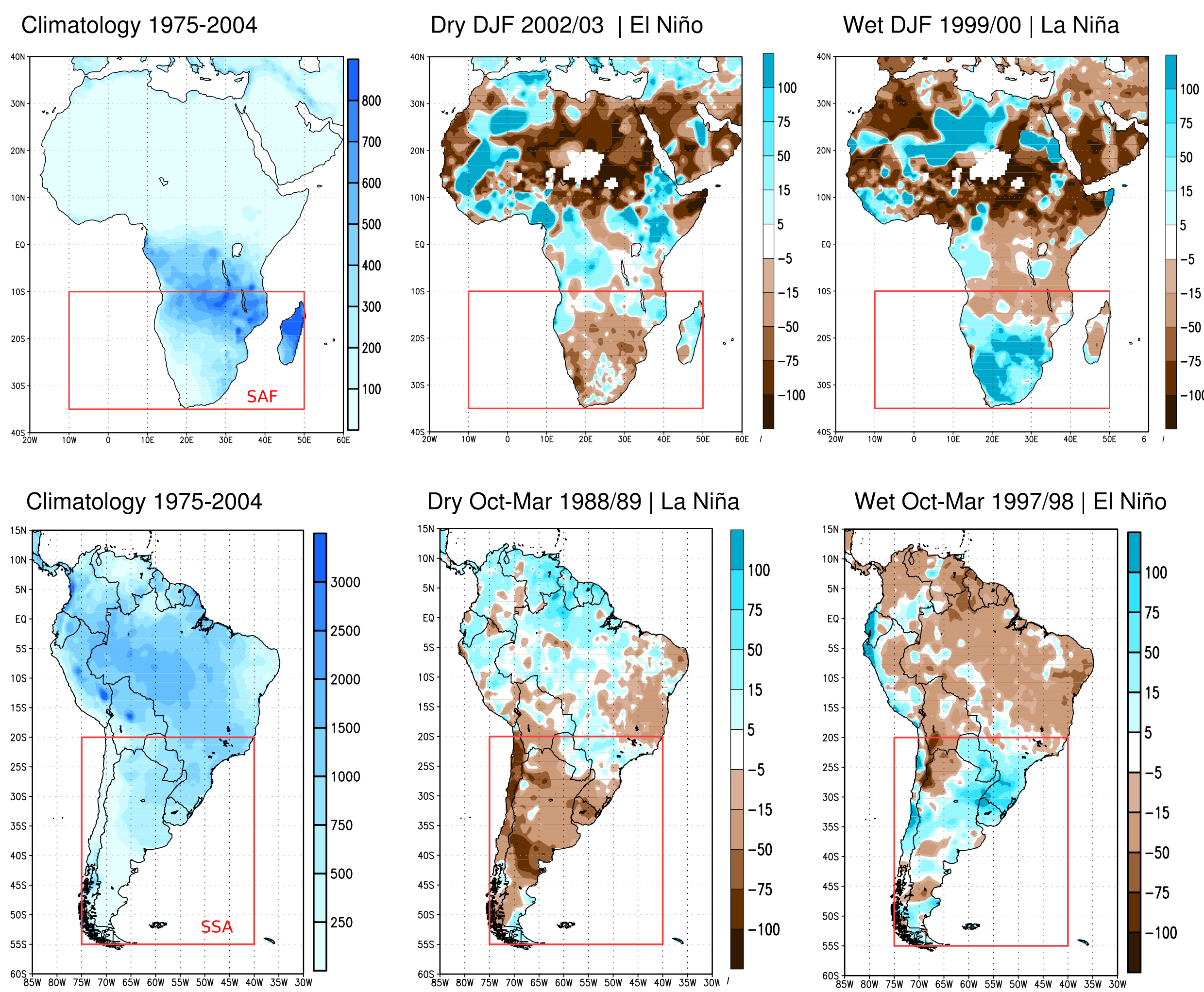

Fig. 1. Mean monthly precipitation of climatology over Southern South America (SSA) and Southern Africa (SAF) for the period 1975–2004 and selected anomalous seasons illustrating a dry and wet season over SSA and a dry and wet season over SAF. The selected seasons occurred during El Niño and La Niña years and had significant impacts on socio-economic sectors in the respective regions.

tropical storms, and tropical cyclones.

The wet event over SAF of 1999/2000 was the result of prolonged heavy rain combined with tropical cyclones Connie and Eline both hitting Mozambique in February 2000 (Hellmuth et al., 2007). Fig. 1 shows above average rainfall across the majority of the selected region, with over 100% anomaly above the climatological average in some areas. In Mozambique alone, the associated flooding affected more than 2 million people, caused 700 deaths, the loss of 350,000 livestock, and economic losses estimated at US$3 billion (Hellmuth et al., 2007). There were, however, some areas, for example, to the north of SAF and in Madagascar that experienced below average rainfall for the season. The DJF 2002/2003 season was, in contrast, relatively dry. There was below average rainfall across most of the region. This lack of rainfall, which followed a drought the previous year (Rouault and Richard, 2005), caused crops to fail and led to food shortages across the region (Bell et al., 2003).

2.2. Southern South America

The SSA region has a high concentration of large urban agglomerations and its economy is based mainly on agriculture, livestock and hydroelectricity production. Moreover most of the La Plata Basin (LPB), one of the world's largest reserves of freshwater, is included in the SSA region. In most of the SSA region the rainy season occurs, on average, from October to March. In this sense, a large part of subtropical South America experiences typical monsoonal circulation ([Kousky, 1988,Zhou and Lau, 1998]). Prominent features include the South American low level jet (LLJ) east of the Andes (Herdies et al., 2002; Marengo et al., 2004), the South Atlantic Convergence Zone (SACZ – [Nogués-Paegle and Mo, 1997, Nogués-Paegle and Mo, 2000]) and the circulation associated with the semipermanent anticyclone over the South Atlantic Ocean (Mächel et al., 1998).

The 1988/89 drought had devastating agricultural effects (e.g. Seiler et al., 1998; Minetti et al., 2007). A recent study (Rivera and Penalba, 2014) concluded that 1988–1989 was one of the most severe drought episodes which affected a great portion of SSA. On the other hand, during 1997 and 1998 the strongest El Niño was registered (National Research Council, 1996; Neelin et al., 2000). In this period positive precipitation anomalies, between 75% and 100% above climatological average, are observed (Fig. 1) across almost the entire SSA region, with the exception of the Patagonia region (around 45°S) and the northwest of Argentina. The maximum precipitation anomalies are found in the LPB area.

3. Methods

The event attribution framework applied follows closely that described in King et al. (2013) with the extension that the attribution study is carried out for both mean precipitation and for the maximum precipitation of five consecutive days (Rx5day, Sillmann et al., 2013). An extended model validation is further carried out to test the ability of the ensemble to represent precipitation variability, considering long-term trends and multiple teleconnections that may drive precipitation amounts in the selected regions. Using identified significant teleconnections, two ensembles of model simulations are constructed, one that represents well the significant teleconnections and another with all the models considered included. Both the comparison of two different seasonal precipitation variables and the comparison of two different ensembles, differing in their consideration of natural variability, allow for exploration of the sensitivity of the attribution statement to these choices. The details of the approach is provided in this section.

3.1. Models, observations and validation

The event attribution is carried out using the general circulation model (GCM) integrations of the Coupled Model Intercomparison Project phase 5 (CMIP5) archive (Taylor et al., 2012). The Rx5day data from these model runs is retrieved from the Expert Team on Climate Change Detection and Indices (ETCCDI) portal, whereas the monthly precipitation data are taken from the CMIP5 archive (Taylor et al., 2012). The Global Precipitation Climatology Centre (GPCC, Becker et al., 2013) observations for mean monthly precipitation and the Hadley Centre EXtreme (HadEX2, Donat et al., 2013) observations for Rx5day are used to validate the models and to determine the intensity of the extreme events. To evaluate the teleconnections between ocean sea surface temperatures (SSTs) and regional precipitation the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST, Rayner et al., 2003) dataset is considered along with both the monthly and Rx5day

Table 1
CMIP5 models considered in the study with number of realisations using the same model physics. The number of realisations are shown for the simulations using all forcings (ALL) and natural forcings only (NAT). The asterix denotes the data related to Rx5day retrieved from the ETCCDI portal. It is available for a reduced set of model realisations shown in the fourth and fifth column only. The last eight columns show the models (crosses) which reproduce the significant relation between seasonal precipitation and Rx5day (⁎) for all the teleconnections considered.

Modelname	ALL	NAT	AL-L*	NA-T*	ENSO SAF	ENSO SSA	Atl3 SAF	Atl3 SSA	EMI SSA	EMI SSA	ENSO SAF*	EMI SSA*
bcc-csm1-1	3	1	3	1					x			
BNU-ESM	1	1			x	x		x		x		
CanESM2	5	5	5	5						x	x	
CCSM4	1	1	1	1		x		x		x	x	
CESM1-CAM5	3	3			x	x			x			
CNRM-CM5	10	6	10	6					x	x	x	
CSIRO-Mk3-6-0	10	5	10	5			x		x		x	x
GFDL-CM3	5	3	5	3			x		x		x	x
GFDL-ESM2M	1	1	1	1		x			x		x	
GISS-E2-H	5	5					x		x	x		
GISS-E2-R	5	1				x	x					
HadGEM2-ES	5	4			x				x			
IPSL-CM5A-LR	6	3	6	3					x		x	
IPSL-CM5A-MR	3	3	1	3	x				x		x	x
MIROC-ESM	3	3							x	x		
MRI-CGCM3	3	1	2	1					x			x
Nor-ESM1-M	3	1	1	1			x		x		x	x

precipitation datasets. The number of models and realisations are summarised in Table 1.

The observations and the models are evaluated for the spatial averages of the regions Southern Africa (SAF) (35–12°S, 10°W–52°E) and Southern South America (SSA) (60–20°S, 75°W–40°W) following the definitions of Giorgi and Francisco (2000). The seasons December–February for SAF and October–March for SSA are used, corresponding to the wet seasons in these regions. The model data are considered over land points only and are regridded to the observational grids. To compute the spatial averages the effective physical grid cell area has been used to take into account the latitudinal gradient.

Before conducting an attribution assessment we evaluate the ability of the model ensemble to represent the precipitation variability over the region (Christidis et al., 2011). The evaluation is here carried out on the long-term trends, interannual variability and spectral decomposition of its variability at different timescales for both mean precipitation and Rx5day for the 100 year period 1905–2004. The means of the model simulations are bias corrected to the mean precipitation from the observations for the climatology of 1975–2004. The HadEX2 dataset for Rx5day is spurious in the beginning of the 20th century with a large number of missing values over both SAF and SSA. The validation and bias correction of Rx5day data is therefore carried out from the time where the number of grid-points where observations are provided is stable. This is from the year 1951 and 1961 for SAF and SSA, respectively.

3.2. Teleconnections of precipitation

In order to determine the impact of teleconnections on the precipitation variability in each region, we analyse how each of three teleconnections influenced precipitation in each region in the past: El Niño Southern Oscillation (ENSO), Atlantic Niño (Atl3) and El Niño Modoki (EMI). The indices were calculated based on the areal means of SSTs of the regions defined in Table 2. For each of these indices the anomaly is calculated for mean precipitation and Rx5day as fractional deviation from the climatology of 1975–2004.

Teleconnections in each region are analysed based on linear regressions of precipitation anomalies and each of the three modes of variability (ENSO, Atlantic Niño and El Niño Modoki), discriminating between positive and negative phases in the observations (HadISST). The Atlantic Niño is an inter-annual mode with a similar pattern as the Pacific counterpart (Zebiak, 1993) and the El Niño Modoki is an alternative phase of the traditional El Niño which evolves over the central Pacific instead of over the Eastern coast. Both modes exhibit a different teleconnection pattern in precipitation (Ashok et al., 2007) and are independent to ENSO. For ENSO we consider a positive and negative phase if the SST anomaly is larger than 0.4 °C and smaller than −0.4 °C, respectively, following the definitions in Trenberth et al. (1997). For the Atlantic Niño and El Niño Modoki the criterion smaller than and larger than 0 °C is used. The significance of each relation is tested with a 5% confidence level.

The same comparison is subsequently performed using the CMIP5 model simulations for the teleconnections that have proven to be significant. As a criterion, it is assessed whether each model correlation is distinguishable from the observed correlation using a test for the difference in the correlation (Olkin and Finn, 1995). The model correlation is calculated by considering all experiments within a model as if they would originate from a single experiment. Performing such a correlation test allows to take into account that each model has a different number of experiments (model years). Models were selected if the correlation was indistinguishable from that of the observations. A model could also be selected if the simulated correlation was not significant as long it was not significantly different from the observed correlation.

This analysis is used to define a reduced ensemble of simulations that selects first only the models that reproduce relevant teleconnections in these regions and second only those years within a 10-year window around the event which are in phase with the teleconnection pattern of the year when the event occurred. Both model ensembles are hereafter distinguished by the non-selective ensembles (ALL and NAT) and ensembles selected to represent the effect of teleconnections (ALL_{TC} and NAT_{TC}).

Table 2
Indices that the describe the teleconnections considered in this study. The indices are computed using regional averages of Pacific sea surface temperature anomalies (SSTA) shown in the third column.

Teleconnection	Abbreviation	Index
ENSO	Niño 3.4 (Trenberth, 1997)	5°N–5°S, 170–120°W Neutral phase within $-0.4\,°C < SST < 0.4\,°C$
Atlantic Niño	Atl3 (Zebiak, 1993)	3°N–3°S, 20°W–0° $SSTA_C - 0.5{*}SSTA_E - 0.5{*}SSTA_W$
El Niño Modoki	EMI (Ashok et al., 2007)	Subscripts refer to Pacific sub-regions Central (C): 10°S–10°N, 165°E–140°W Eastern (E): 15°S–5°N, 110–70°W Western (W): 10–20°N, 125–145°E

3.3. Attribution of extreme events

To determine how anthropogenic forcings influence precipitation, we compare the natural (NAT) and all forcings (ALL) and the ensembles selected by precipitation teleconnections (NAT_{TC} and ALL_{TC}) at the time of each event. Each event is represented using a 10-year window centred around the year of the event, assuming that the models are close to stationary during the length of such a period. The wet event over SAF during 2002/2003 is constructed with 6 years only due to the limit of the CMIP5 historical simulations which end in 2005.

The following analysis is carried out for both ALL and NAT, and ALL_{TC} and NAT_{TC}. A Kolmogorov–Smirnov test is first carried out to determine if samples drawn for ALL and NAT are significantly different. A gamma distribution is estimated for the ALL and NAT samples, as this has been shown to be an adequate representation of both mean and Rx5day precipitation (Husak et al., 2007). An extreme value distribution might arguably be the correct representation of a sample of maximum data such as Rx5day, yet consideration of spatial averages would no longer preserve the maximum stable properties and hence the same distribution as for mean precipitation is used. These distributions are used to evaluate how the exceedance probability of the precipitation amounts observed in each event changes between ALL and NAT. This is done by calculating the Fraction of Attributable Risk (FAR – Allen, 2003), defined as $1 - P_{NAT}/P_{ALL}$, where P_{ALL} and P_{NAT} are the probabilities of the threshold being exceeded in the ALL and NAT ensembles, respectively. For the wet events this is the probability that the observed event or wetter occurred, whereas for dry events this the probability that the observed event or drier occurred.

The uncertainty of the FAR is estimated by bootstrapping each sample 1000 times, before fitting the data to gamma distributions to give a representation of the uncertainty that arises from limited ensemble sizes. The FAR is only considered significant if the confidence bounds given by the 5th and 95th percentiles exclude a value of zero.

4. Results

4.1. Evaluation of simulated precipitation from 1905 to 2004

The ability of the CMIP5 models to represent precipitation variability over SAF and SSA is shown in Fig. 3(a) and (b), respectively. Over SAF a negative long-term trend was observed for mean precipitation (0.5 mm/day per decade) and a positive trend for Rx5day (0.45 mm/day per decade) which were both reproduced by the ensemble including anthropogenic forcing. This finding is consistent with previous studies, yet some regional long term changes might be obscured by considering a regional average over Southern Africa (Kruger, 2006). A strong long-term increase in mean precipitation was observed over SSA (1.8 mm/day per decade) as shown in previous studies (Barros et al., 2008; Penalba and Robledo, 2005) which was not captured in the ensemble of CMIP5 models. It is therefore questionable if the ensemble is an adequate representation of precipitation over the SSA region. Individual models showed a significant positive trend but were only able to represent at most half of the observed precipitation trend. The median trend of ALL was larger than that of NAT, which may indicate that some of the observed trend is attributable to anthropogenic forcings (Vera and Diaz, 2014). For Rx5day as over SAF a positive trend was observed (2.5 mm/day per decade) which is contrary to the seasonal precipitation reproduced by the ensemble mean of CMIP5 models including anthropogenic forcings.

The validation of precipitation interannual variability shows an overall uniform picture. The interannual variability, as well as its spectral decomposition for different time-scales, is captured well by the model ensemble over both regions. There is some indication that the ALL ensemble represents the variability more accurately. Little evidence of significant multi-year variability in the observations was detected. The results hold for both mean precipitation and Rx5day. The variability of both variables is close to Gaussian, which may simply be due to spatial averaging according the central limit theorem. This indicates that even a Gaussian distribution could be adequate to represent the model ensembles to compute changes in the distribution. However, using a gamma distribution ensures that the probability of having negative precipitation values is zero which is physically more consistent.

4.2. Precipitation teleconnections and representation in CMIP5 models

The relation of the selected teleconnection patterns with seasonal precipitation is illustrated in Fig. 2. A significant teleconnection signal emerges between the positive and negative phases of ENSO (El Niño events for SSA and La Niña events for SAF). Several studies have documented a relationship between extreme precipitation events and El Niño over SSA (e.g., Rao and Hada, 1990; Pisciottano et al., 1994; Grimm et al., 2000; Ropelewski and Bell, 2008; Grimm and Tedeschi, 2009) and with La Niña over SAF (Lindesay et al., 1986; Nicholson and Entekhabi, 1987; Tyson and Preston-Whyte, 2000). Significant relationships are also identified between the observed precipitation anomalies and the tropical Atlantic Niño (based on Atl3 index) as well as for the El Niño Modoki in the Tropical Pacific.

For Rx5day a significant relationship during La Niña events emerges over SAF, illustrating higher extreme precipitation rainfall as identified for the mean seasonal precipitation. Stronger extreme precipitation amounts are also found for positive phases of EMI for SSA. Apart from these no significant relationships between the teleconnection modes and the Rx5day data has been found, which might be a consequence of having shorter lengths of the records.

In order to select the GCMs which are able to represent teleconnections on the precipitation variability in each region, the same analysis as with observations is performed for each of the models. The models which are able to capture a significant correlation between the indices and the regional precipitation amounts are denoted with a cross in Table 1. The overall picture is diverse. All the models are able to reproduce at least one teleconnection, but none are able to capture all the teleconnections over both regions. Clustering the teleconnections into the two regions shows that no model can be selected that captures all relevant teleconnections for SAF, whereas only two models capture all teleconnection over SSA. This finding inhibits a selection of models that capture the tropical teleconnections that appear to explain part of the precipitation variability in the two study regions. In order to account for at least part of the natural variability we choose as a compromise a selection of models based only on ENSO mode, which explains the largest fraction of variability at the inter-annual scale (Deser et al., 2010; Doblas-Reyes et al., 2013). This leaves a selection of four and five models for SAF and SSA, respectively, which provide sufficient samples to estimate the distributions of precipitation to compute probabilities of exceedances.

4.3. Attribution of Southern African dry and wet events

The distributions of FAR for the SAF events are illustrated in Fig. 4a and show that anthropogenic influences increased the risk of the 2002/2003 drought event significantly, as the 5th to 95th confidence bounds lie above zero FAR. This is the case for non-selective (based on ALL and NAT) and for the selective (based on ALL_{TC} and NAT_{TC}) distributions. The distribution is shifted higher for the selective distributions, yet the uncertainty in FAR increases as fewer models and years of data are available to compute the probabilities of exceedances in the selective ensemble. The Kolmogorov–Smirnov test (KS-test) is only significant for the non-selective ensemble consistent with the finding based on the bootstrapped confidence interval of FAR which indicates only significant non-zero values in the non-selective case. The median value of FAR for the non-selective distributions is 0.3, which is equivalent to stating that around a third of the risk of the event occurring is attributed to anthropogenic causes, respectively.

For the wet event of 1999/2000 the FAR distributions are shown for both the mean seasonal precipitation and Rx5day. The FAR distributions show median values for the mean seasonal precipitation below zero in both cases (-0.8 for non-selected and -0.5 for selected ensemble), which for both ensembles indicates that anthropogenic impacts decreased the risk of the wet event occurring. FAR is not designed to quantify the proportion of risk attributable in cases where the risk reduces, nevertheless we retain this measure for means of comparability. This result for the wet event is significant for the non-selective ensemble while for the selective ensemble, the uncertainty of FAR exhibits a greater spread (due to the smaller ensemble size) and the 95th percentile is slightly above zero. The KS-test again confirms that the distributions are different only in the non-selective case.

Using the Rx5day data the median FAR values lie above zero for both ensembles. This indicates that anthropogenic forcings have increased the likelihood of high precipitation totals in a short period of time. However, this result is not significant at the 5% level given the wide confidence bounds in FAR. The KS-test by contrast indicates that the ensembles NAT and ALL are drawn from different distributions in both the non-selective and selective case. Hence while we find reduced risk in observing anonymously wet seasons in terms of seasonal totals there is some tentative indication that the risk to observe extreme precipitation over five consecutive days may have increased.

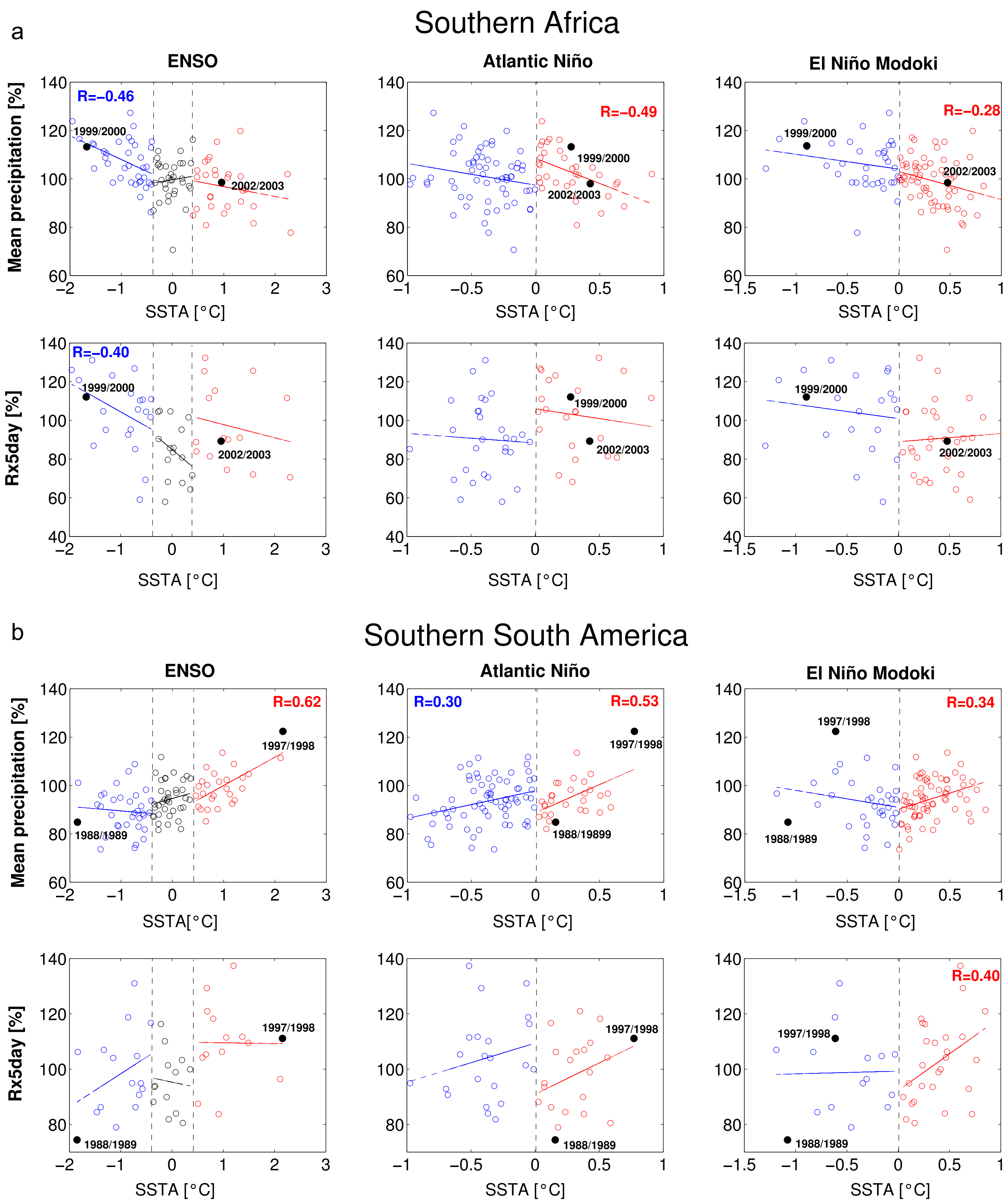

Fig. 2. Linear regressions of teleconnection indices (ENSO (Trenberth, 1997), Atlantic Niño (Zebiak, 1993) and El Niño Modoki (Ashok, 2007)) with precipitation anomalies as percentage of mean precipitation over Southern Africa (a) and Southern South America (b) for mean precipitation and maximum precipitation of five consecutive days (Rx5day). The anomalies are computed as fractional deviations from the climatology 1975–2004 for mean precipitation for Rx5day over Southern Africa and Southern South America, respectively. For Rx5day shorter periods were used due to lack of data in the early century (1951–2004 for SAF and 1961–2004 for SSA). The regressions are computed for positive (red), neutral (black, only ENSO) and negative (blue) phases of the indices and significant regressions are highlighted with a correlation coefficient. The black dots show the selected events for the respective regions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

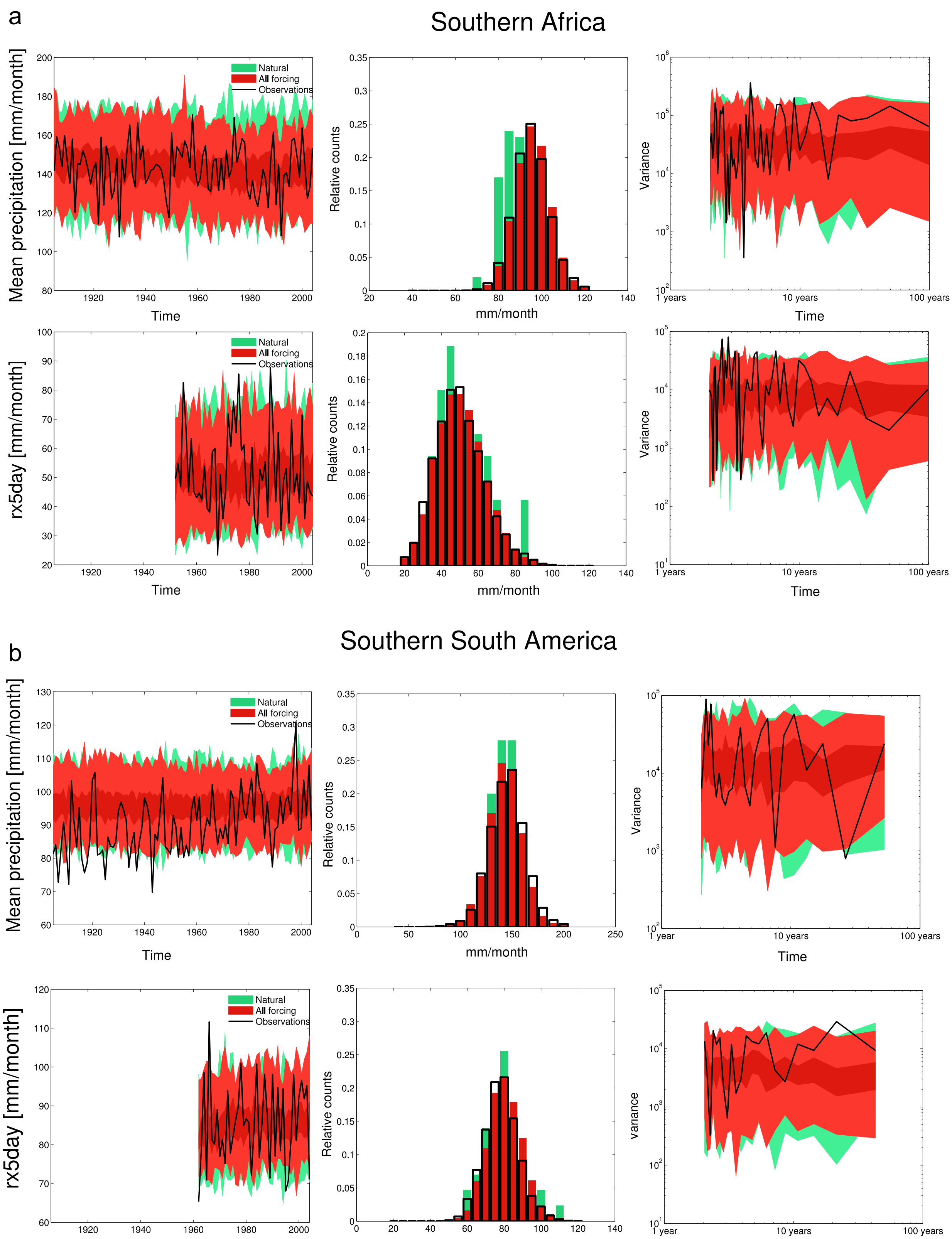

Fig. 3. Precipitation variability of CMIP5 models using all forcings (red) and only natural forcings (green) compared to observations of mean precipitation (GPCC) and Rx5day (HadEX2) for Southern Africa (a) and Southern South America (b). The individual panels show in the first column long term trends, in the second column interannual variability from the detrended series as histograms and in the third column the spectral decomposition of the variability for different time windows in years. The figures are computed for the period 1905–2004 for mean precipitation and 1951–2004 for Rx5day. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

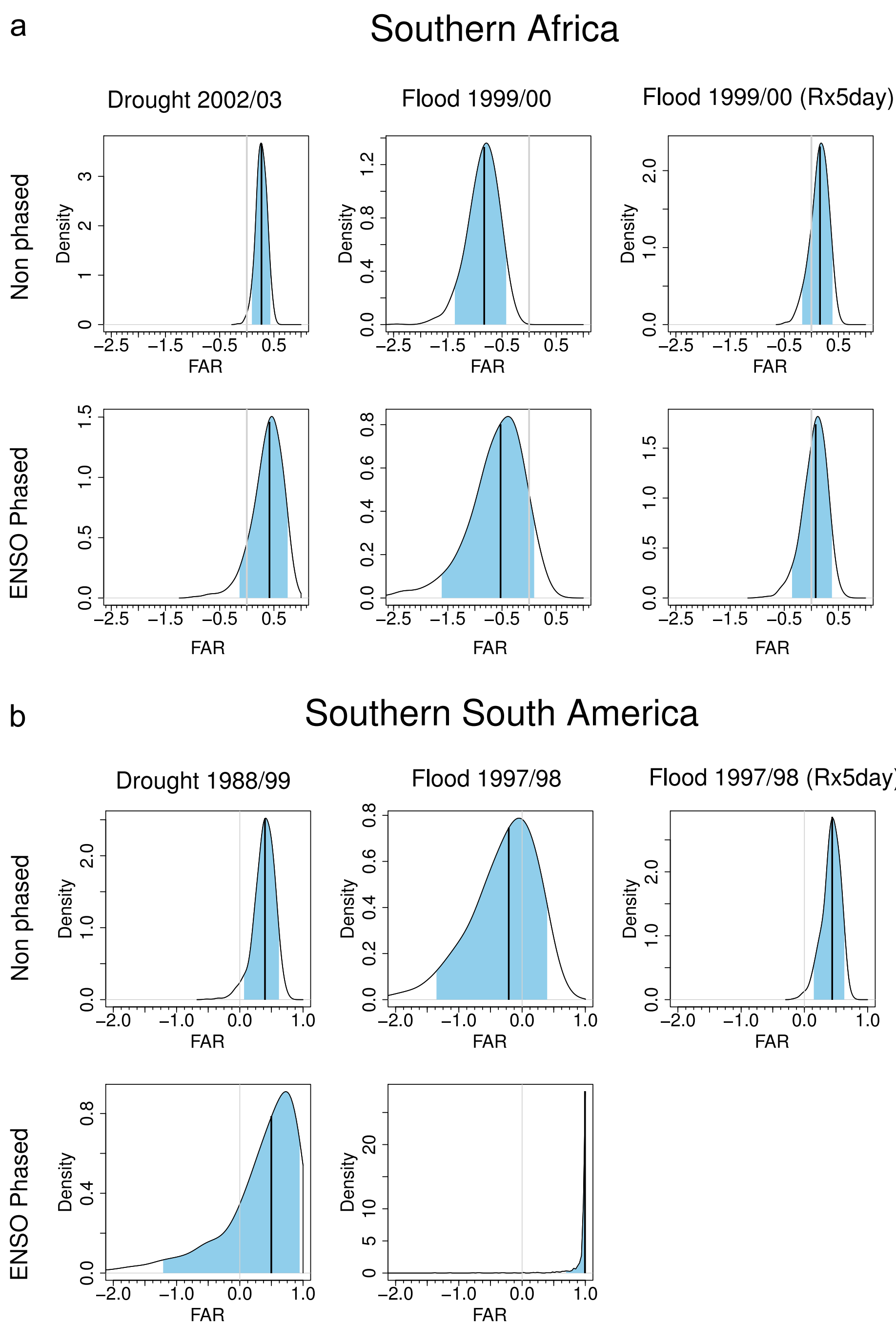

Fig. 4. Empirical distributions of Fraction Attributable Risk (FAR) for the period DJF in Southern Africa (a) and October to March in Southern South America (b) for the selected events. Each of the region distributions of FAR are shown using all models years (Non phased) and only model years which are in the same phase of ENSO when the event occurred. Blue shading indicates range of 5th to 95th percentiles of the distribution of FAR using bootstrapping of the model data and the black line the median. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.4. *Attribution of South American wet and dry events*

The same analysis as over SAF is performed over SSA, bearing in mind that the observed long-term trend of seasonal precipitation is not adequately represented by the CMIP5 models. The models do though capture well the past variability of Rx5day. The overall picture is similar to SAF. For the drought event (1988/1989) there are positive FAR values which are only significant in the non-selective case, with a median of 0.4. In the selective case the confidence bounds widen with lower numbers of model years and thus zero FAR can no longer be excluded. However, KS-tests applied to the drought event do show a significant difference between the ALL and NAT and ALL_{TC} and NAT_{TC} ensembles.

For the wet event of 1997/1998, both monthly precipitation and Rx5day indices were analysed. For the seasonal mean precipitation amounts the ensembles without the model selection show a FAR distribution that has a median value of -0.25, suggesting that the likelihood of this event was decreased due to anthropogenic influence. However, the 95th percentile of this distribution is greater than zero, indicating no significant FAR. The KS-test confirms this finding by indicating identical parent distributions. A negative median FAR is unexpected in this context as there is some indication for a positive trend in ALL as discussed in (Vera and Diaz 2014). Since the flooding event over SSA falls in the very high tails of the model distributions (130 mm/month, see Fig. 3b) a gamma distribution might though no longer adequately represent the probabilities (Papalexiou et al., 2013).

The limitation of the approach to attribute such an extreme event becomes fundamentally difficult for the case where the ensembles were selected with respect to ENSO where the samples of model years is approximately ten times smaller. The event occurs with a probability close to zero in the reduced ensembles NAT_{TC} and ANT_{TC}, which are unable to capture such an extreme event. The event is hence highly unlikely in both ensembles but results in a value FAR of one with a negligible confidence bound, as the probability in ANT_{TC} is, albeit being almost zero, still order of magnitudes larger than NAT_{TC}. The interpretation would be that the event would have been nearly impossible in world without climate change even though the probability of the event is extremely small in both ensembles. This example illustrates a limitation of the approach when selecting model ensembles that are limited in size which results in an under-dispersive representation of underlying variability of highly extreme events. The underlying uncertainty of FAR is a consequence not represented adequately and the resulting value of FAR should hence not be interpreted physically.

For the Rx5day index, in this case, there were no significant ENSO relations identified. Therefore only one pair of ALL and NAT ensembles was analysed as no selection of simulations with respect to a teleconnection could take place. The median value of FAR for this case was found to be 0.4, which is significant and the KS-test confirms that the two ensembles were drawn from different distributions. Hence while there are weak grounds to determine attributable risks for seasonal precipitation over SSA based on the methodology adopted we find that an extreme precipitation event as occurred in 1997/1998 has become more likely due to anthropogenic influences.

5. Discussion and conclusions

We have presented an application of event attribution for dry and wet rainy seasons over Southern Africa and Southern South America, studying events which have caused high socio-economic impact in terms of flooding or droughts. The analysis comprised the use of GCMs from CMIP5 which include all atmospheric forcings (anthropogenic and natural) and natural forcings only, in order to estimate how human activity has changed the odds of occurrence of such events. The application is further extended to explore how natural drivers associated with different modes of the Southern Oscillation affect the attribution results.

The event attribution results show that the risk of dry austral summers (DJF) over Southern Africa (SAF) such as during the years 2002/2003 was increased due to human influence. However, the risk of a wet summer as occurred during 1999/00 was decreased.

The CMIP5 models are, in contrast to over SAF, unable to represent the precipitation variability over Southern South America (SSA). Mean precipitation during the rainy season (October to March) has increased over SSA in the last century, which is only weakly captured by the models including anthropogenic forcings. Attribution statements about the events are thus questionable with the set of model simulations considered in this study. Bearing in mind these shortcomings, little significant contribution of human activity could be identified on wet and dry events for seasonal precipitation as occurred during the austral summers 1997/98 and 1988/89, respectively. As over SAF we find evidence for an increased risk of high 5-day extreme rainfall totals during the flooding event of 1988/89.

Precipitation over both SAF and SSA prove to be correlated with the phase of ENSO but also modes of the Atlantic Niño and the El Niño Modoki. Since there is no subset of models contributing to CMIP5 that is able to represent all of the relevant of the teleconnections a subset of models based on solely ENSO was selected. This selection represents an intermediate approach between event attribution studies using models with prescribed SSTs (Pall et al., 2011; Schaller et al., 2014) and non-initialised models (King et al., 2013; Lewis et al., 2014) which are able to simulate coupled processes between the atmosphere and the ocean. Considering the models which are in phase with ENSO when the events occurred and simulate coupled atmosphere–ocean processes has found to change weakly the magnitude of FAR but not its sign. However, the differences are obscured by increased uncertainty in FAR as the selected sample of model years that include ENSO is smaller in comparison to all the model data available in CMIP5.

The alternative evaluation of the wet season using an extreme index for precipitation (Rx5day) indicates (not significant at the 5% level) that the odds of experiencing short and intense precipitation events increased over SAF in contrast to a decreased chance of having a wetter mean season due to climate change. This finding is consistent with previous studies arguing that an increase of the water holding capacity due to increasing temperatures leads to more intense precipitation events while seasonal mean precipitation decreases in subtropical regions (Held and Soden, 2006). For the wet event over SAF during 1999/00 (which was affected by prolonged precipitation and two tropical cyclones, causing severe damages due to flooding) both mean seasonal precipitation and Rx5day may seem an adequate representation of the event, yet result in different attribution statements. This example highlights the different conclusions that can arise by asking different questions on the attributable risk of an extreme event.

Finally, we find that the uncertainty in the fraction of attributable risk using bootstrapping of the confidence intervals can be large, in particular when few data points are available, but still allows for several significant statements.The uncertainty of FAR increases particularly if the event is very rare, i.e. if it lies in the tail of model distributions, and thus the attributable risk using this framework is generally more uncertain for very extreme events, for instance the heavy precipitation levels in 1997/98 over Southern South America.

Concluding our findings in SAF we find an increase in risk of anomalously dry austral summer seasons and an increase in risk of anomalously wet seasons attributable to anthropogenic influence on climate. For SSA, model deficiencies mean we are not able to make a robust attribution statement about changes of risk of anomalously wet October–March seasons as seen in 1997/98 or anomalously dry October–March seasons as seen in 1988/89. Thus, though we have been able to make some strong statements pertaining to changes in the risks in Southern Africa, further work is needed to more precisely quantify the fraction of risk attributable to anthropogenic and natural factors in Southern South America.

Acknowledgements

We acknowledge the World Climate Research Programme (WCRP) and the International Centre for Theoretical Physics (ICTP), which supported this research through the WCRP-ICTP Summer School on Prediction and Attribution of Extremes (2014). The work of Bellprat and Ciavarella was further supported by the EUropean CLimate and weather Events: Interpretation and Attribution (EUCLEIA), funded by the European Union's Seventh Framework Programme [FP7/2007-2013] under grant agreement no. 607085. The contribution of Lott was supported by the Climate Science for

Service Partnership through the Newton UK–China Research and Innovation Partnership Fund, while Stott was supported by the Joint DECC/Defra Met Office Hadley Centre Climate Programme (GA01101). The work of Gulizia was supported by the Argentina National Council for Scientific and Technological Research [CONICET PIP 11220120100586]. The work of Parker was supported by the National Environmental Research Council (NERC) under Grant NE/K005472/1.The Hadley Centre authors (Ciavarella, Lott and Stott) would also like to thank the other authors and their supervisors for allowing the time to work on this study.

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